The Impact of Conflict on Children Nutritional and Health Outcomes : The case of Farmer-Herder Conflict in Nigeria

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Abstract.

Armed conflict exposure in early childhood could be especially debilitating because apart from the direct impact of the exposure, an armed conflict event could indirectly threaten child wellbeing through insufficient food security (George et al., 2020), destruction of infrastructure, and loss of family member(s). The farmer-herder conflict in Nigeria has received little attention due to the conflict's typically low-intensity nature (Moritz, 2010) and other major conflict events such as the Boko Haram conflict in Nigeria. However, the farmer-herder conflict has risen in recent years yet very few studies have been conducted on the impact of the farmer-herder conflict. Moreover, studies reveal that (Shemyakina 2011; De Walque and Verwimp 2010; Mercier et al., 2016) the impact of conflict varies within the same population based on individual and household characteristics. Since farmer-herder conflict events primarily occur within farming communities, we expect that farm households are likely to experience disproportionate conflict impact. We are not aware of any studies conducted on the heterogeneity in the impact of farmer-herder conflict on the nutritional and health outcomes of children from farm households. Hence, this study aims to analyze the impact of the farmer-herder conflict in Nigeria on the nutritional and health outcomes of children from farm households.

We used a triple difference method to analyze the main objective of this study. The datasets used in this study come from the Armed Conflict Location & Event Data Project (ACLED) and the Nigeria Demographic and Health Surveys (DHS) 2018. The ACLED (Raleigh et al., 2010) dataset provides real-time information on farmer-herder conflict events in Nigeria between 1997 – 2022. The information contained in the ACLED dataset includes conflict locations geocoordinates, conflict actors, and the number of fatalities for each farmer-herder conflict event. The Nigeria 2018 DHS dataset is a cross-sectional dataset which provides information on households’ demographic and health indicators including children's dietary intake and anthropometric measures. The Nigeria DHS sample was selected by employing a stratified two-stage cluster design. The first stage sampling units are clusters, which are selected using probability proportional to the cluster size. The second stage involved selecting 30 households per cluster using equal probability systematic sampling. The Nigeria DHS 2018 dataset consists of information on 1389 clusters and 40,387 households. Using conflict locations geocoordinates obtained from the ACLED dataset and clusters geo coordinates from the Nigeria DHS dataset we

identified 226 clusters within 15km distance of the farmer-herder conflict events. Since conflict is non-random, we employed caliper matching to match 93 conflict-exposed clusters to 93 unexposed clusters based on cluster-level geographic and socio-economic covariates that may influence a cluster's exposure to conflict events.

We exploit the spatial and temporal variation in conflict events to identify the conflict-exposed clusters. We define conflict-exposed clusters as clusters that have experienced at least one conflict event within a year before the time of the DHS survey in the cluster and are within a 15km exposure radius of the conflict event. We define farm households in the study as households where at least one of the spouses engages in an agricultural occupation. We used children's minimum dietary diversity score (MDDs) as a measure of children's food security while we used children's WHZ, and HAZ scores as measures of underweight, wasting and stunting in children respectively. We exploit the temporal variation in conflict events and children’s date of birth to classify children between 0-59 months old into two cohorts: alive during conflict and born after conflict cohorts to capture the difference in anthropometric measures between the two cohorts. Further, to capture the contemporaneous impact of conflict on children's dietary diversity we classified conflict-exposed clusters into those surveyed during conflict events and those surveyed after conflict events are over in the cluster.

We used the “children’s birth cohort” variable, the “clusters conflict exposure” variable, and the “farm households” variable that indicates whether the child is from a farm household or non-farm household as the first, second, and third differencing variable in our triple difference model used in analyzing the impact of conflict on the anthropometric measures of children from farm households. However, we substituted the first differencing variable for the “survey during conflict” variable in the triple difference model when analyzing the impact of conflict on the MDDs of children from farm households. To mitigate selection bias in this study, we ensured conflict-exposed clusters and unexposed clusters are balanced based on cluster-level characteristics that may affect conflict exposure in the cluster such as average household wealth index and average household head education level. Further, we included fixed effects in the triple difference model using a strata variable that has unique values for each conflict exposed cluster and its corresponding unexposed cluster to correct for unobserved heterogeneity. Clusters in the

DHS are displaced to maintain the anonymity of the respondents; hence, we used a Monte Carlo simulation to test the robustness of our result.

Our findings show that conflict contributes to childhood underweight and stunting of children from farm households. However, the conflict has no statistically significant impact on children's wasting and dietary intake. On average, conflict reduces children's WAZ and HAZ scores by approximately 2.34 and 2.28 respectively. Given that the WAZ score and HAZ score of an average child that is unexposed to conflict in the sample is about -0.7 and -1.1 respectively, the result implies that, on average, exposure to the conflict would cause a child to be severely underweight or stunted or both. Our results are robust to the inclusion of several matching covariates to the original matching covariates used in obtaining the study's results. Moreover, our results are robust to using the number of conflict events in a cluster as an alternative conflict exposure variable. There are a few limitations to the findings of this study. Reverse causality poses a threat to causal inference in our study. Conflict may affect children's nutritional and health outcomes; however, these outcomes may also determine conflict exposure in the cluster. The implication of using cross-sectional data for this study is that our findings are specific to the impact of farmer-herder conflict on nutritional and health outcomes in 2018 and they are not generalizable to other periods.

The impact of conflict on children's nutritional and health outcomes: The case of farmer-herder conflict in Nigeria. (Job Market Paper)

1. Introduction

Early childhood shock could have a devastating impact on a child's nutritional and health outcomes (Akresh et al., 2011) as well as socioeconomic outcomes in adulthood (Akresh et al., 2017; Maccini and Yang, 2009). This impact could be further exacerbated through lingering effects if the shock affects the household's labor and physical assets (Mercier et al., 2016), which is usually the case with conflict shocks. Studies (Ghobarah et al., 2004; Gates et al; 2012; and Beyrer et al., 2007) have shown that conflict indirectly contributes to an increase in mortality rate by impeding the development, access, and resources available to the healthcare sector. Further, conflict promotes the development of chronic diseases and the spread of communicable diseases through internal displacement, disruption of food supply chain, mental stress, gender-based violence, and destruction of social infrastructures.

Armed conflict exposure in early childhood could be especially debilitating because apart from the direct impact of the conflict exposure through loss of household members and income, an armed conflict event could indirectly threaten child wellbeing through food inaccessibility (George et al., 2020) and destruction of social infrastructures. Moreover, children exposed to conflict during early childhood are more likely to exhibit stunting, which may affect an individual's long-term economic productivity (Akresh et al., 2011). Farmer-herder conflict is one of the major conflicts that has been ongoing in Nigeria over the last few decades (Raleigh et al., 2010). The farmer-herder conflict has received little attention due to the conflict's typically low-intensity nature (Moritz, 2010). Moreover, other conflict events in Nigeria such as the Boko Haram conflict in the northwest and the Niger Delta Avengers conflict in the southeast of Nigeria have diminished attention to the farmer-herder conflict, leading to limited studies on its impact.

However, the farmer-herder conflict has risen in recent years. In 2018 alone, the farmer-herder conflict accounts for almost 2000 fatalities, which is over 20 per cent more fatalities compared to those related to the Boko haram conflict in Nigeria (Matfess, 2018). Further, the drivers of the farmer-herder conflict in Nigeria, which include droughts (Madu and Nwankwo, 2020), high population (International Crisis Group, 2018) are expected to increase over time (Shiru et al., 2020; United Nations, 2019) Hence, it is imperative to understand the impact of the conflict and mechanism through which it affects households exposed to the conflict. This paper aims to address this issue by evaluating the impact of Nigeria's farmer-herder conflict on child's nutritional and health outcomes.

This study made three main contributions to the growing literature on violent conflict and food security. Firstly, to the best of our knowledge, this is the first study carried out to assess the impact of farmer-herder conflict on children's welfare in Nigeria. This study utilizes a fine-grained analysis to assess the impact of conflict on children's nutrition and health outcomes, specifically evaluating the effects on both short-term dietary diversity and long-term indicators such as weight-for-age, wasting and stunting. The study employs the DHS dataset, which includes 24-hour food recall information for children. This allows for an analysis of conflict's impact on child nutrition and an investigation into whether dietary diversity serves as a pathway linking conflict to long-term nutritional and health outcomes in children.

Secondly, the study used the DHS dataset, which provides information on households' clusters geo-coordinates in conjunction with the ACLED dataset, which contains information on farmer-herder conflict locations geo-coordinates to more precisely identify conflict-exposed clusters using their distance to conflict locations. Due to the non-randomness of conflict events, the study employed multiple matching techniques to match conflict-exposed clusters to non-exposed clusters based on constructed cluster level variables that may affect clusters exposure to conflict as well as children nutritional and health outcomes.

Lastly, the impact of conflict can vary depending on individual and household characteristics such as gender, level of education, residential location, and wealth status within the same population (Shemyakina 2011; De Walque and Verwimp 2010; Mercier et al., 2016). Moreover, the farmer-herder conflict events primarily occurs between pastoralists and farmers in host communities, which suggests that farm households living in conflict-exposed clusters may experience a different impact of conflict compared to non-farm households in the same clusters. An understanding of the heterogeneity in the impact of farmer-herder conflict can aid policymakers in developing targeted policies and allocating resources effectively. Hence, using the DHS dataset, which provides information on both farm and non-farm households, this study examines the heterogeneity in the impact of conflict on nutrition and health outcomes of children living in both households.

This study used cross-sectional data which was obtained from the Nigeria 2018 Demographic Health Survey (DHS) and the Armed Conflict Location and Event Data (ACLED) to evaluate the impact of farmer-herder conflict in Nigeria on children's minimum dietary diversity score (MDDS), weight-for-age Z scores (WAZ), weight-for-height Z scores (WHZ), and height-for-age Z scores (HAZ). Conflicts do not occur haphazardly, and their occurrence may be correlated to some of the factors affecting children's MDD, WAZ, WHZ, and HAZ score such as household poverty level. Thus, we checked the mean difference between households living in conflict-exposed clusters and unexposed clusters on observable variables that could affect household's exposure to conflict and outcome variables (MDD, WAZ, WHZ, and HAZ scores) used in the study. Based on these variables, our findings show that households located in conflict-exposed clusters are not significantly different from households that are in unexposed clusters.

We used a difference-in-difference model, which exploits the spatial and temporal variation in the farmer-herder conflict event as well as the temporal variation in the timing of children's birth as our baseline model in this study. The MDD scores of children living in conflict-exposed clusters where conflict is ongoing at the time of the survey are compared to their counterparts while the WAZ, WHZ, and HAZ scores of children that were alive during conflict living in conflict-exposed clusters are compared to their counterparts. Moreover, due to the nature[1] of the farmer-herder conflict, there may be heterogeneity in conflict impact between farm and non-farm households. Hence, this study employed a triple difference approach using farm household as third differencing variables.

Based on past studies on the impact of conflict on children's nutritional and health outcomes and the anecdotal reports discussed in the literature review section on the impact of farmer-herder conflict in Nigeria. Our first hypothesis is that conflict have a negative impact on children food security in general due to increase in food prices through the disruption of food

[1] The farmer-herder conflict events often directly involve Fulani herders and farmers from other ethnic groups.

supply chain, and the impact would be more severe for children living in farm households. However, our hypothesis may not hold if the impact of the conflict on the food supply chain is either minimal or transient, or if households exhibit resilience and are able to quickly recover, leading to a return of children's dietary intake to pre-conflict levels prior to the household survey

Since farmer-herder conflict is reported to not only affect the food supply chain but also destruction of social infrastructure, we hypothesize that conflict may also affect the health outcomes of children living in all households. Hence, conflict may have an impact on children’s WAZ and WHZ scores, which are measures of short-term nutritional and health outcomes in children. The second hypothesis is that conflict would negatively affect children’s WAZ scores and WHZ scores, but the impact would be more profound for children from farm households.

Lastly, fatalities and destruction of farm assets due to farmer-herder conflict in farming communities my cause loss of farm household members and income loss. Hence, we hypothesize that farm households may not only experience a more severe conflict impact but also a more lasting impact of conflict compared to non-farm household. Further, since HAZ score is a measure of long-term nutritional and health outcomes of children, our fourth hypothesis is that children conflict affects the HAZ scores of children from farm households and have no effect on children living in non-farm households.

The rest of this paper proceeds as follows. In the background section, the state of children’s nutritional and health outcomes, and farmer-herder conflict in Nigeria were discussed. The ACLED and DHS dataset used in the study as well as the spatial and temporal variation of the farmer-herder conflict events are discussed in the data section. The next section discussed the empirical strategy used in the study, followed by a discussion of the results.

2. Background

Dietary diversity, undernourishment, wasting and stunting of children under five years of age in Nigeria.

Over the past decade, there has been a steady increase in malnutrition across the globe, more than one in every 10 people are severely food insecure in 2020 (FAO, 2021). Increasing food prices and income inequality were cited as the major factors driving inaccessibility to a healthy diet among 3 billion people in 2019 (FAO, 2021). About 12.6 % of the Nigerian population does not consume enough food to meet the minimum daily calorie requirement (World Bank, 2018

A child's minimum dietary diversity (MDD) score to a certain extent, reflects the nutritional sufficiency of a child's diet (FANTA, 2006; Kennedy et al., 2007; Mirminiam et al., 2004; and Arimond et al., 2010). The MDD score is the count of selected food groups that the child is reported to have consumed in a 24-hour dietary recall (Kennedy et al., 2011). Using the WHO (2010) guideline, we constructed an MDD score comprising of 8 food groups[2] for infants and young children between 6-23 months old. Another MDD score including 9 food groups[3] was constructed for children between the age of 24-59 months old based on the FAO guidelines (Kennedy et al., 2011) for measuring individual dietary diversity score (IDDS).

Weight for age Z-score (WAZ), weight for height Z-score (WHZ), and height for age Z-score (HAZ) are anthropometric measures that represent children's long-term nutritional and health outcomes. The WHZ score is a measure of wasting and the HAZ score is a measure of stunting, and they reflect acute and chronic undernutrition respectively while the WAZ score is a measure of underweight, which reflects both acute and chronic undernutrition. Some of the consequences of poor dietary intake include wasting and stunting, both often resulting from acute and chronic malnutrition, respectively. A child is considered to be wasted if her weight for height score is more than two standard deviations lower than the median weight for height of children between 0- 59 months of an international reference population. In addition, a child is said to be stunted if her height for age score is more than two standard deviations lower than the median height for age of children between 0 - 59 months of an international reference population.

According to the World Bank (2018) between 4 - 14% of children living in sub-Saharan Africa are wasted, while Nigeria has a relatively lower percentage of about 6.8% of children under five years of age who are wasted. Wasting can usually be rectified after a period of a

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[2] The 8 food groups included in the MDDS of children between 6-23 months old are grains, root and tuber; legumes and nuts; dairy products; flesh foods; eggs; vitamin-A rich fruits and vegetables; and other fruits and vegetables, and breast milk. The WHO guideline was update in June 2017 to include breast milk as an 8th food group in the infant and young children MDDS.

[3] The 9 food groups are starchy staples, dark green leafy vegetables; other vitamin A rich fruits and vegetables; organ meat; other fruits and vegetables; meat and fish; eggs; legumes, nuts, and seeds; and milk and milk products.

healthy dietary intake. However, stunting has irreversible consequences on a child's physical and mental ability in the long term, if the condition is not corrected in the first 1000 days from conception (Roser and Ritchie, 2019). About 20 - 50 per cent of children under 5 years of age living in sub-Saharan Africa are stunted, Nigeria is on the higher end of the spectrum with 36.8% of its population of children under 5 years of age stunted (World Bank 2018). Inadequate nutritional intake and infection due to poor sanitary practices among other factors have been identified as one of the major causes of stunting and wasting in children under 5 years old.

The farmer-herder conflict in Nigeria

The farmer-herder conflict as the name may suggest, is a conflict usually between pastoralists of Fulani ethnic background and sedentary farmers from other ethnic groups. The conflict is primarily driven by increased competition for land resources, which is further exacerbated by local politics with an ethnic-religion aspect. Several factors contribute to the conflict, including encroachment on grazing corridors by sedentary farmers and the government due to population growth and urbanization (Benjaminsen, 2012). Land demands for residential, industrial, and agricultural purposes have led to an increase in encroachment of grazing corridors (Peace, 2017).

Other factors include growing desertification, increasing temperature and longer duration of dry season due to climate change and the Boko-Haram conflict events in the northern part of the country has led to a significant reduction in pastures available to Fulani herders causing them to migrate farther south or relocate permanently to the central region of the country (PEACE, 2017). Some of how Boko haram contributed to the farmer-herder conflict event was through occupying grazing corridors and poaching of herders' livestock which forces the farmer to migrate more southwards for pasture in areas where they typically do not graze their cattle.

Boko Haram insurgents have been reported for poaching livestock from Fulani herders as well as occupying territories that were once grazing corridors for the herders. In addition to migrating more frequently and to areas farther south of the country, Fulani herders extend the length of the grazing season in host communities to avoid Boko Haram insurgents, which consequently facilitates tension and hostilities between the herders and the residents of the host communities (George et al., 2021).

The farmer-herder conflict is responsible for about 8000 reported fatalities over the last decade (Raleigh et al., 2010). In 2018, which was the height of the conflict, farmer-herder conflict events are reported to have led to around 2000 fatalities in Nigeria, particularly in the north-central zone of the country (Raleigh et al., 2010). Figure A3 and A4 reveals that five states located in the north-central and northeastern regions of Nigeria account for about 80 per cent and 87 per cent of farmer-herder conflict events and fatalities in 2018 respectively. This has resulted in the agricultural productivity decline and increased rural poverty rates in the north-central region of the country.

The farmer-herder conflict led to about a 33 to 65 per cent decline in agricultural production in three major food-producing states in the north-central region of Nigeria in 2018 (ICG, 2018). Further, because these states are often considered the food basket of the nation, conflict events could potentially lead to a countrywide increase in food prices and issues in agribusiness operations. At the national level, Mercy corps (2015) estimated that in the absence of farmer-herder conflict in four states in the north-central region of Nigeria, revenue would increase by $13.7 billion per annum, which is about 2.8 per cent of Nigeria's GDP. The farmer-herder conflict has resulted in a significant amount of internal displacement, with an estimated 300,000 individuals affected (Nnoko-Mewama, 2018). Furthermore, the conflict has led to the destruction of approximately 7000 hectares of agricultural lands (Bukari, 2017).

3. Data and Description

To estimate the impact of the herder-farmer conflict in 2018 on child nutrition and health outcomes, we use the Demographic Health Survey (DHS) 2018 data, which is nationally representative data from a survey conducted among Nigerian households from August 2018 to December 2018. Locations, where the 2017/18 farmer-herder conflict events occurred, were included in the DHS survey. The DHS dataset provides information on food consumption, birth date, height, and weight of children under 5 years old, which were used in the construction of cohorts and outcome variables.

In addition, the DHS survey includes both agricultural and non-agricultural households, this helps to compare how the farmer-herder conflict affects agricultural households and non-agricultural households. According to Akresh et al., (2012), households' residential location during the survey period might be different from the residential location during the conflict period, hence, having information on household residence location during the period of conflict is essential to identify the households that are exposed to conflict. The DHS dataset provides information on how many years a household has lived in the current residence, using this information we can identify the households that lived in the current residence during the time of conflict.

We also use the ACLED data (Raleigh et al., 2010), which provides real-time information on conflict incidence, fatalities, actors as well as the geographic location of the conflict. Using geospatial information on household clusters obtained from the DHS dataset and conflict locations obtained from ACLED data (Raleigh et al., 2010), each conflict location was matched to clusters within a 15km radius of the conflict location using geodetic distances.

The geospatial information reported in the DHS data is not entirely accurate due to geo-scrambling. This technique is used to protect respondents' confidentiality by randomly displacing the geographical locations of clusters. Urban clusters are displaced by 2km, while rural clusters are displaced by 5km. However, this random displacement may lead to measurement errors in studies that rely on this data. Specifically, it may result in inclusion errors if unexposed clusters are randomly displaced into the specified conflict exposure radius, or exclusion errors if exposed clusters are randomly displaced outside of the conflict exposure radius. Thus, misclassification of clusters as being either exposed or unexposed to conflict is possible.

To minimize the impact of measurement errors caused by geo-scrambling, we used a 15km conflict exposure radius around each conflict location as a buffer. This buffer increases the likelihood that the true locations of conflict-exposed clusters fall within the defined conflict exposure radius. However, there may be instances where the true location of conflict-exposed clusters closer to the exposure radius boundary falls outside the conflict exposure radius. Similarly, clusters outside the 15km buffer distance (i.e., unexposed clusters within proximity to the conflict exposure radius boundary) may be mistakenly classified as exposed. This implies that while the buffer helps to reduce measurement errors, it is not perfect and may still result in misclassification of exposed or unexposed clusters in some cases.

To resolve this issue, the distance of an exposed urban cluster to a conflict location should be at least 2km lesser than the conflict exposure radius specified while there should be at least a 2km distance between a conflict exposure radius and an unexposed urban cluster. The same also applies to exposed and unexposed rural clusters; the only difference is that the buffering distance is 5km instead of 2km. For instance, for a 15km specification radius, exposed urban clusters should be at most 13km away from the conflict location while exposed rural clusters should be at most 10km away from the conflict location. However, including a distance buffer implies that some treated and good control clusters are going to be dropped from the sample.

The spatial and temporal pattern of the 2018 Farmer-Herder conflict events.

Although the farmer-herder conflict has been ongoing for decades, historical data reveals a seasonal pattern to the event. The event usually starts around the beginning of the harmattan season[4] and peaks around January the following year before gradually declining. Figure A1 reveals the temporal variation in the 2017/18 farmer-herder conflict events. The farmer-herder conflict peaks in January 2018 with over 400 conflict incidences before gradually declining to lower than 100 conflict incidences in August. The number of fatalities seems proportional to the number of conflict incidents except between March to June when there are spikes in the number of conflict fatalities.

While all regions in Nigeria have experienced farmer-herder conflict at some point in time, the conflict is concentrated in the north-east and north-central regions of Nigeria as shown in Figure A2. The states of Nasarawa, Taraba, Benue, Plateau, and Adamawa, situated within the region, are accountable for approximately 80% of the farmer-herder conflict incidents that occurred in 2018. As depicted in Figure A3, each of these states recorded over 40 conflict events in 2018. The states mentioned above in addition to Kaduna state account for over 90 percent of all farmer-herder conflict fatalities in Nigeria in 2018, with over 100 fatalities in each state.

Conflict exposed clusters and matched clusters

Conflict exposed clusters are clusters that are within a 15km radius of conflict locations while clusters that are not within the specified radius are classified as unexposed clusters. In exposed clusters, children are grouped into two birth cohorts based on whether they are born after the last conflict event in the cluster or alive during the conflict period in the cluster. The

[4] The harmattan season is a period characterized by low humidity and high temperature; it begins around the end of November and ends in the middle of March.

birth cohort variable takes the value of "1" if children are alive before the cluster's last conflict event and takes the value of "0" if children are born after the last conflict event in the cluster. Thus, conflict-exposed children are children who are alive during conflict and are living in conflict exposed clusters at the time of survey.

The study's difference in difference framework relies on the hypothesis that the difference in the WAZ, WHZ, and HAZ scores of children who are alive during conflict living in exposed clusters and other children in the sample is conflict. This is not the case when assessing the effect of conflict on children's MDD scores since the MDD score is based on a child's dietary intake 24 hours before the survey. For instance, the difference between the MDD score of a child born after conflict and another that is alive during conflict living in a cluster that is not undergoing conflict at the time of the survey is most likely not due to conflict. To understand how conflict affects MDD scores, instead of comparing birth cohorts, children living in clusters that are undergoing conflict are compared to those living in clusters that are not undergoing conflict at the time of the survey. Further, children that are living in matched unexposed clusters are grouped into two groups based on whether their cluster strata are undergoing conflict at the time of the survey.

Table 1: Descriptive table for independent variables

Independent variables	Description	Expected signs
Exposed cluster	Dummy variable that takes the value of "0" if household cluster is outside 15km radius of conflict location and takes the value of "1" if the household cluster is within 15km radius of conflict location.	+/-
Farm household	Dummy variable that takes the value of "0" if neither the household head nor is or her spouse is engaged in agricultural occupation and takes the value of "1" if either the household head or his/her spouse is engaged in agricultural occupation	-
Alive during conflict	Dummy variable that takes the value of "0" if a child was born after conflict and "1" if the child was alive during conflict	+/-
Child's age	Age of the child in months	+/-
Female child	Dummy variable that takes the value of "0" if a child is male and "1" if the child is female	+/-
Household head age	The age of the household head in years	+
Female household head	Dummy variable that the value of "0" if a household head is male anidd "1" if the household head is female	+/-
Household size	The number of household members living in the household at the time of survey	+/-
Number of children	The number of children living in the household at the time of survey	-
Household head years of education	The number of years household head spent in obtaining a formal education	+
Mother's education level	Mother's level of education	+
Household wealth index	Composite wealth measure based on household assets (Television, refrigerator, motorcycle, car, and land) ownership adjusted for household region (rural/urban)	+
Number of conflict incidences	The number of conflict incidences in a cluster	-
Number of conflict fatalities	The number of conflict fatalities in a cluster	-
Semiannual period lapsed	The number of six-month periods that have elapsed since the last conflict event in the cluster before September 2017	-
Month of birth	The child's month of birth	
Month of interview	The month that survey was conducted in the cluster	

4. Empirical strategy

To estimate the causal effect of farmer-herder conflict on children's MDD, WAZ, WHZ, and HAZ scores, the study exploits the spatial variation in the conflict events and variation in conflict exposure across birth cohorts. The study used two models; the first model is a difference in difference approach, which relies on the assumption that, on the average, children's MDD, WAZ, WHZ, and HAZ scores would follow the same time trend in conflict-exposed clusters and unexposed clusters if there were no farmer-herder conflict events. Hence, the study's baseline model is a difference-in-difference model, which takes the following form:

$$y_{ihjcs} = \beta_o + \beta_1 Post_{ij} + \beta_2 Exposed_c + \beta_3 Post_{ij} * Exposed_c + \beta_4 W'_{ihjcs} + \beta_5 X'_{hcs} + \beta_6 Z'_{cs} + \delta_c + \theta_j + e_{ihjcs} \quad (1)$$

Where y_{ihjcs} is the MDD, WAZ, WHZ, or HAZ score of a child *i* living in household *h* in cohort *j* located in cluster *c* in cluster strata *s*.

$Post_{ij}$ is 1 if child i in cohort j is alive during conflict when the outcome variables are WAZ, WHZ, and HAZ scores or 1 if cluster is undergoing conflict at the time of interview when the outcome variable is MDD score.

$Exposed_c$ is 1 if cluster *c* is within 15km of conflict exposure radius.

W'_{ihjcs} is a vector of children characteristics.

X'_{hcs} is a vector of household-level characteristics.

Z'_{cs} is a vector of cluster-level characteristics.

δ_c is cluster exposure fixed effect.

θ_j is the birth cohort fixed effect.

e_{ihjcs} is the error term.

Certain factors in the cluster, both during and post-conflict, could have an impact on the WAZ, HAZ, and WHZ scores of children. To account for this, we use a birth cohort fixed effect,

θ_j, which helps control for time invariant unobserved trends that could potentially influence the outcome variables. Further, we also included children month of birth fixed effects to the model to control for more potential confounding factors such as seasonal changes in food availability, disease prevalence, and household income.

The cluster exposure fixed effects, δ_c, controls for time invariant unobserved factors within clusters, which may affect children outcome variables. In addition, unobserved factors specific to the state, region and rurality of a cluster could affect both conflict incidence in the cluster and the outcome variables used in the study, thus biasing the estimates obtained from the analysis. To correct for this potential bias, the study includes cluster strata fixed effects.

$$\begin{aligned} y_{ihjcs} = \beta_o + \ \beta_1 Post_{ij} + \ \beta_2 Exposed_c + \beta_3 Post_{ij} * Exposed_c \\ + \beta_4 W'_{ihjcs} + \beta_5 X'_{hcs} + \beta_6 Z'_{cs} + \delta_c + \theta_j + \ \tau_s + e_{ihjcs} \end{aligned} \tag{2}$$

Where τ_s is cluster strata fixed effects.

The study employs a triple difference approach using agricultural households as the third differencing variables. As discussed in the background section, the farmer-herder conflict events often directly involve farmers and herders. Hence, the study assumes conflict impact would differ across households in conflict-exposed clusters based on the occupation of the household head or household head's spouse.

$$\begin{aligned} y_{ihjcs} = \beta_o + \ \beta_1 Post_{ij} + \ \beta_2 Exposed_c + \ \beta_3 \ Farmhousehold_{hcs} + \ \beta_4 Post_{ij} \\ * Exposed_c \ + \ \beta_5 Post_{ij} * \ Farmhousehold_{hcs} + \ \beta_6 \ Exposed_c \\ * \ Farmhousehold_{hcs} + \ \beta_7 Post_{ij} * Exposed_c * Farmhousehold_{hcs} \\ + \beta_8 W'_{ihjcs} + \beta_9 X'_{hcs} + \beta_{10} Z'_{cs} + \delta_c + \theta_j + \ \tau_s + \ \gamma_h + e_{ihjcs} \end{aligned} \tag{4}$$

$Farmhousehold_{hcs}$ takes the value of "1" if household head or household head's spouse of household h located in cluster c in cluster strata s has an agricultural occupation.

γ_h is farm household fixed effect.

Our identification strategy relies on the parallel trend assumption, which implies that in the absence of conflict there are no difference between the outcome variables of children who are living in conflict-exposed clusters and those living in unexposed clusters. To prove the parallel trend assumption, we did a regression of the outcome variables[5] on the interaction term of conflict exposure and children's age in months for children in born after conflict cohort. Table 2 below shows that there is no statistically significant difference in children's outcomes between children living in conflict-exposed clusters and those living in unexposed clusters across age in the born after conflict cohort.

Table 2: Regression for parallel trend assumption

	WAZ	WHZ	HAZ
Conflict exposure	-0.484	0.614	0.0938
	(-0.66)	(0.92)	(0.12)
1-2 months old * Conflict exposure	0.536	-0.435	-0.799
	(0.59)	(-0.53)	(-0.84)
3-4 months old * Conflict exposure	0.539	-0.925	0.214
	(0.55)	(-1.06)	(0.21)
Over 4 months old * Conflict exposure	0.544	-0.459	-0.0471
	(0.57)	(-0.54)	(-0.05)
Constant	-0.0150	0.313	-0.549
	(-0.03)	(0.72)	(-1.07)
Observations	108	106	107

Conflict events do not occur haphazardly; hence, conflict exposed clusters might have certain characteristics that differentiate them from clusters that are not affected by farmer-herder conflict. To address this potential source of endogeneity, we explored seven matching strategies in the study using average household head years of education in the cluster, average household wealth index in the cluster, percentage of non-Fulani households in the cluster, cluster strata, and percentage of farm households in the cluster as matching variables. For the purpose of this study we discussed the caliper matching scenario used in our analysis while the other six matching strategies attempted in this study are further discussed in the Appendix B Section.

[5] The majority of children belonging to the cohort born after the conflict are less than 5 months old and predominantly rely on breastfeeding. Therefore, in the regression analysis, the outcome variables did not incorporate children IDDS as there was insufficient data on 24-hour food recall for most children within the cohort.

Caliper matching

Unexposed clusters are randomly matched to conflict exposed clusters within +/- specified caliper width of matching covariates' values without replacement. A strata variable is generated such that matching covariates values are within the same +/- caliper width for all matched clusters in each stratum. One potential drawback of the caliper matching method is that it employs a greedy match algorithm to match unexposed clusters to conflict-exposed clusters. This implies that the first group of conflict-exposed clusters would be matched to all possible unexposed clusters that fit the matching criteria, resulting in conflict-exposed clusters not being matched to unexposed clusters despite the availability of potential unexposed clusters in the sample. To prevent this occurrence, the maximum number of unexposed clusters matched to each conflict exposed cluster is restricted to one.

Table 3 displays the difference in means between the matching covariates in the exposed clusters and unexposed cluster using the caliper matching sample. Of the 575 households in the caliper matching sample, 60% are in conflict-exposed clusters. Further, matching covariates are balanced between the conflict-exposed and unexposed clusters. The caliper-matching sample was used for the main regression analysis presented in this study because it provides the most balanced sample in terms of the matching covariates with a relatively large sample size. The 575 households are located in 186 clusters across 19[6] states in Nigeria. The total number of children in the sample is 885 with 592 living in conflict exposed households while 293 lives in unexposed households.

[6] The 19 states in the sample are Katsina, Adamawa, Kaduna, Nasarawa, Plateau, Taraba, Benue, Kogi, Oyo, Osun, Ekiti, Ondo, Edo, Anambra, Enugu, Ebonyi, Cross river, Bayelsa, Delta, and Ogun state. According to ACLED (2010), 22 of the 36 states in Nigeria reported farmer-herder conflict events in 2018.

Table 3: Caliper matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
Farm households	0.361	0.290	-0.030
	(0.481)	(0.454)	(0.021)
Household wealth index	3.065	2.936	-0.083
	(1.332)	(1.377)	(0.062)
Household head years of education	5.206	5.144	0.006
	(1.347)	(1.284)	(0.085)
Rural households	0.370	0.304	0.000
	(0.484)	(0.461)	(0.000)
Number of children	293	592	885
Number of households	230	345	575
Number of clusters	93	93	186

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents the description of the independent variable used for the analysis in this study along with their expected signs while Table A1 reports the summary statistics of both the dependent and independent variables used in this study. The average minimum dietary diversity score of children in the study falls below the required minimum of four points, which shows that the dietary intake of children in the sample is not diverse enough to meet their nutritional needs. Table A2 also shows that on the average children in the sample are not underweight, wasted or stunted. The average age of children in the sample is about 2 years old and sample has almost equal amount of female and male children. Mothers in the sample have low education attainment with the average mother's highest education level not exceeding secondary school.

The sample consists of non-Fulani households with about one-third being farm households. The average household in the sample is a middle-income household. On the average, household heads in the sample spent about five years in school and only 15% of the household heads are female. On the average, a household has six members and two children. Additionally, roughly one-third of the households in the sample belong to rural clusters. Moreover, the households in the sample have experienced an average of two conflict events and six conflict fatalities in their clusters.

5. Results

The first column in Table A3 reports the difference in difference estimation of the effect of conflict on children's dietary diversity score. The second column reports a similar analysis but with control for individual, household, and cluster-level characteristics. The estimates reported in the third and fourth columns on the impact of farmer herder conflict on the dietary diversity score of children living in farm households. Similarly, the last two columns in Table A3 report the effect of conflict on children living in farm households with a month of survey fixed effects.

Findings show no statistically significant difference in the dietary diversity of conflict-exposed children compared to unexposed children. The result in the first column shows that conflict has no impact on the dietary diversity of children living in exposed clusters. Further, the survey during conflict and exposed cluster interaction variable suggests that conflict has no contemporaneous effect on child dietary diversity. This finding is robust to the inclusion of children, household, and cluster variables. Moreover, results in the last four columns of Table A3 also reveal no difference in dietary diversity of children living in conflict–exposed farm households compared to their counterparts.

The findings reported above imply that conflict has no long-term or contemporaneous impact on children's dietary diversity irrespective of whether they live in farm households or not. This contradicts our hypothesis that conflict affects children's dietary diversity particularly children living in farm households. One reason for this contradiction could be that children are given special diets that are different from other household members since their health tend to be more vulnerable to poor nutritional intake. The DHS dataset does not provide information on household dietary intake, but it reports food consumed by mothers 24 hours before the DHS survey.

On the one hand, a mother's dietary diversity is a pathway through which conflict may affect a child's nutritional and health outcomes. Nursing or pregnant mothers who do not get enough nutrition may negatively affect their children's nutritional status (Nguyen et al., 2012; FAO, 2016). On another hand, a mother's dietary diversity tends to reflect her child's dietary diversity (Amugsi et al., 2015) since they typically live in the same household. Hence, conflict's impact on the mother's nutritional status could be a proxy that helps to check the robustness of our findings as well as a means to examine whether children are given a special diet in the household. Results reported in Table A8 show that conflict has no impact on mothers' dietary diversity. Another reason why conflict does not have an impact on a child's dietary diversity score could be that the impact of conflict on the food supply chain and food prices is for a short period such that households are resilient in the short term and the shock does not affect household consumption pattern.

However, older children have slightly less dietary diversity than younger children. Similarly, children who live in larger families have marginally lower dietary diversity than those who live in smaller households. In contrast, children who live in non-poor homes have higher dietary diversity compared to their counterparts. Studies (Codjoe et al., 2016; Muche et al., 2016) have shown that children living in male-headed households tend to do better than their counterparts living in female-headed homes in terms of dietary diversity due to differences in earning capacity of male-headed and female-headed families. However, our findings suggest that there are no differences in dietary diversity between children living in female-headed households and those living in male-headed households.

The first column in Table A4 reports the difference in difference estimation of the effect of conflict on a child's weight-for-age Z-score. The second column reports a similar analysis but with control for individual, household, and cluster-level characteristics. The analyses estimates reported in the third and fourth columns reveal the impact of farmer-herder conflict on the weight-for-age Z-score of children living in farm households. The last two columns in Table A4 show the impact of farmer-herder conflict on children living in farm households with a child's month of birth fixed effect.

Findings show that conflict has a negative impact on the WAZ scores of children living in farm households, however, conflict does not have any statistically significant impact on children's WAZ scores in general. Results in columns 1 and 2 show that children who are alive during the conflict have lower weight for age Z-scores than their counterparts, this does not imply that conflict affects all children that are alive during the conflict period since not all children that are alive during conflict live in clusters that are not exposed to conflict. In addition, living in conflict-exposed clusters have no impact on children's WAZ scores. Similarly, being alive during conflict and living in a conflict-exposed cluster has no impact on children's WAZ scores. In fact, the inclusion of the farm household variable as a third differencing variable in the models reported in columns 3-6 shows that children who are alive during conflict living in exposed clusters have higher WAZ scores than their counterparts. This result suggests that living in a conflict-exposed location and being alive during conflict does not determine whether a child would be negatively affected by conflict.

The triple difference estimates reported in column 4 reveal that being alive during conflict and living in farm households located in conflict-exposed clusters, on average, reduces children's WAZ score by approximately 2.68. Although, this estimate decreased with the inclusion of control variables and increased slightly to 2.34 with the inclusion of children's month-of-birth fixed effects in the model. Given that the average children's WAZ score in the sample is -0.7, the result implies that, on average, exposure to the conflict would make an average child in the sample to be severely underweight i.e., the child's WAZ scores would drop from -.7 to -3.04.

Given the nature of the farmer-herder conflict, we expect farm households to be disproportionately affected; this finding is corroborated by studies (Bruck et al., 2016; Mercier et al., 2016; Baliki et al., 2017) on the heterogeneity of conflict impact among subgroups in the population. Factors contributing to the disproportionate conflict impact experienced by farm households may include the loss of household members and the destruction of farm assets and inventories. These factors could determine the severity and persistence of the conflict's impact on farm households and their resilience to the conflict.

It is important to note that living in a conflict location and being alive during conflict does not imply that children are negatively affected by conflict, likewise, does living in farm households located in conflict locations. As results in columns 3-6 show, children that are alive during conflict living in farm households are not statistically significantly different from their peers in terms of WAZ scores. These findings imply that households located in conflict locations may not necessarily experience a direct negative shock due to the conflict if household members are engaged in non-agricultural occupation since most conflict events are centered around farming communities. Further, indirect conflict shock experienced by non-farm households through an increase in food prices or disruption of the food supply chain is likely to be minimal or transitory such that it does not have any long-term impact on the nutritional or health outcome of children living in these households.

Moreover, column 3 in Table A4 reports that children who are living in farm households located in conflict-exposed clusters have higher WAZ scores. This finding is consistent with the inclusion of children, household, and cluster variables as controls in column 4. It is also robust to the addition of children's month of birth fixed effects in column 6. This implies that children who are born after the conflict in farm households located in conflict locations have better health outcomes. This could imply that while the impact of conflict on farm households is severe and sustained, farm households may recover after the conflict period. Further mother's education level and household wealth index positively affect children's WAZ score. Studies (Abuya et al., 2012; Mensch et al., 2019; Amah & Woldemanuel, 2021) have found that children whose mothers have a higher maternal education level have higher anthropometric measures compared to their counterparts.

The first column in Table A5 reports the result of the baseline model for the impact of conflict on wasting among children. The baseline model with control for individual, household, and cluster-level characteristics was reported in the second column. The third and fourth columns in Table A5 reveal the result for the analysis of the impact of farmer herder conflict on child wasting among children living in farm households while the last two columns report similar models with children's month of birth fixed effects. Results show that conflict has a negative but no statistically significant impact on wasting among children in the sample including those living in farm households. Further, older children have slightly higher WHZ scores. Finally, children in clusters with a higher incidence of conflict have higher WHZ scores, while those living in clusters with higher conflict fatalities have lower WHZ scores than their counterparts.

There are a couple of possible reasons for this seemingly ambiguous result. First, not all conflict events result in fatalities; hence, clusters exposed to one or more conflict incidence may not have any reported conflict fatalities. Thus, explaining the difference in the impact of the number of conflict incidence and conflict fatalities on child wasting. Moreover, as previously discussed, given the nature of the farmer-herder conflict events, disparities in conflict impact are expected. Hence, children living in clusters with higher conflict incidence may have higher WHZ scores if the conflict does not have a direct significant and lasting impact on their nutrition and health.

Table A6 reports the regression estimates for the impact of conflict on stunting among children. Our findings indicate that conflict has a profound and detrimental impact on the stunting of children from farm households, however, this effect is not observed among the general population of children in the sample. Thus, indicating that the impact of conflicts on child stunting is specific to farm households, this finding is similar to the result reported on the impact of conflict on children's WAZ scores in Table A4.

The first column in Table A6 reports that children that are alive during the conflict have lower HAZ scores compared to their counterparts and the second column shows that this result is robust to the inclusion of control variables. This result may suggest that households, where children are alive during conflict, have less than ideal socio-economic conditions compared to households where children were born after conflict. However, results reported in Table A2 indicate that the socio-economic conditions of both household groups are similar. Findings reveal in the first two columns reveal that neither living in an exposed cluster nor being alive during conflict and living in an exposed cluster has a statistically significant impact on children's HAZ scores. However, the inclusion of farm households in the model reported in column 3 shows that children that are alive during conflict and are from conflict-exposed clusters have higher HAZ scores than their counterparts and this result is consistent with the addition of control variables in the models reported in columns 4 to 6.

Further, children who are alive during the conflict from farm households located in conflict-exposed clusters have lower HAZ scores. These result remains consistent when controlling for children, household and cluster level variables and month of birth fixed effects. This result suggests that being alive at the time of conflict and being present in an area where conflict occurs is not enough for children's HAZ scores to be affected. It appears that children also need to be living in farm households to experience a more direct and sustained conflict impact sufficient to affect their HAZ scores.

Given that children in the sample have an average of -1.05 HAZ score, the magnitude of the impact of conflict reported in column 6, which is approximately -2.5, implies that on average conflict decreases a child's HAZ score by over 200% relative to the average HAZ score of a child in the sample. Moreover, this magnitude is sufficient to make a child with an average HAZ score to be severely stunted. Similar to what we observe on the effects of living in farm households exposed to conflict on children's WAZ scores, it seems that children who are born after conflict living in conflict-exposed farm households have better WAZ outcomes than their counterparts do. This could indicate that farm households recover after the conflict ends in their cluster.

Our results also show that for every one-month increase in children's age, their HAZ scores fall by .0007. Hence, older children are more likely to be stunted than their younger counterparts are. Children living in non-poor households have higher HAZ scores. Moreover, female children have higher HAZ scores compared to male children. Studies (Wamani et al., 2007; Ali et al., 2017; Thurstan et al., 2020) on gender disparities in anthropometric measures among children under five years old in sub-Saharan Africa corroborate this finding. We also find that HAZ scores of children living in conflict-exposed clusters increase by about 0.12 for every conflict event that occurs within five years before households were surveyed. This result could suggest that conflict does not have a negative and sustained impact on children living in conflict-exposed clusters except for those from farm households.

Sensitivity Analysis

Figures A5 and A6 report the baseline estimates for conflict impact on children's WAZ and HAZ scores, respectively and the corresponding estimates obtained from the alteration of the original matching method and the triple difference regression model used in the study. Two main methods were employed to assess the robustness of the estimates obtained from the analysis of the impact of conflict on children's WAZ and HAZ scores. The first method introduces potential matching variables one at a time into the set of original covariates used for caliper matching. The second method substitutes the conflict exposure variable in the regression model for the variable reporting the number of conflict events.

Figure A5 shows that the regression estimate on the impact of conflict on a child's WAZ score is robust to include the following variables in the matching covariates used in the caliper-matching scenario. The variables added to the matching covariates include the average agricultural land size in the cluster, the average proportion of land ownership among households in the cluster, the average education level of mothers in the cluster, the average education level of household head in the cluster, or average proportion of households who own a car or motorcycle in a cluster. Moreover, the baseline estimate in Figure A5 is also robust to the substitution of clusters' conflict exposure variable in the baseline model for the total number of conflict incidences in a cluster.

The sensitivity analysis for the impact of conflict on HAZ scores of children living in farm households is reported in Figure A6. The analysis estimate is robust to substituting the conflict exposure variable with the number of conflict events in a cluster variable in the triple difference regression model. Further, the analysis estimate is robust to adding matching covariates such as the average agricultural land size in the cluster, the average proportion of land ownership among households in the cluster, the average education level of mothers in the cluster, or the average education level of household head in the cluster to the original matching variables used for the baseline analysis.

Mechanism of farmer-herder conflict impact

Tables A7 and A8 report the impact of conflict on factors that are potential pathways through which conflict affects the child's nutritional and health outcomes analyzed in this study. A channel through which conflict may affect a child's nutritional and health outcomes is access to professional healthcare. Table A7 reports the impact of conflict on mothers' prenatal care and the number of antenatal visits made by a mother. The result shows that conflict negatively affects mothers' receiving of prenatal care in farm households. However, conflict does not significantly affect the number of antenatal visits made by a mother.

Further, Table A8 reports the impact of conflict on factors preventing mothers' healthcare access. Compared to their counterparts, conflict-exposed mothers living in farm households often cite financial issues and not wanting to travel alone as reasons for not visiting a healthcare facility when ill. However, they are less often to indicate the distance to a healthcare facility as a reason for not seeking medical attention.

The DHS dataset does not provide information on household dietary intake, but it reports food consumed by mothers 24 hours before the DHS survey. Mother's dietary diversity is a pathway through which conflict may affect a child's nutritional and health outcomes. Nursing or pregnant mothers who do not get enough nutrition may negatively affect their children's nutritional status (Nguyen et al., 2012; FAO, 2016). Studies (Huang et al., 2017; Hassan et al., 2017) have also shown that low maternal dietary diversity is associated with wasting and stunting in children.

Since they typically live in the same household, a mother's dietary diversity tends to reflect her child's dietary diversity (Amugsi et al., 2015). Hence, conflict's impact on the mother's nutritional status could be a proxy and evidence that supports our findings on the impact of conflict on a children's dietary diversity. Results reported in Table A8 show that conflict has no impact on mothers' dietary diversity. These findings suggest that the channel through which farmer-herder conflict affects the weight and height of children living in farm households is not their dietary intake but access to health care.

Conclusion

This paper analyzes the impact of farmer-herder conflict on children’s nutritional and health outcomes using a difference in-difference analysis and a triple difference approach to examine the heterogeneity of impact on children from farm households. Our findings show that while conflict have a pronounced negative effect on the WAZ score and HAZ score of children from farm households, it does not seem to have any impact on children in the sample in general.

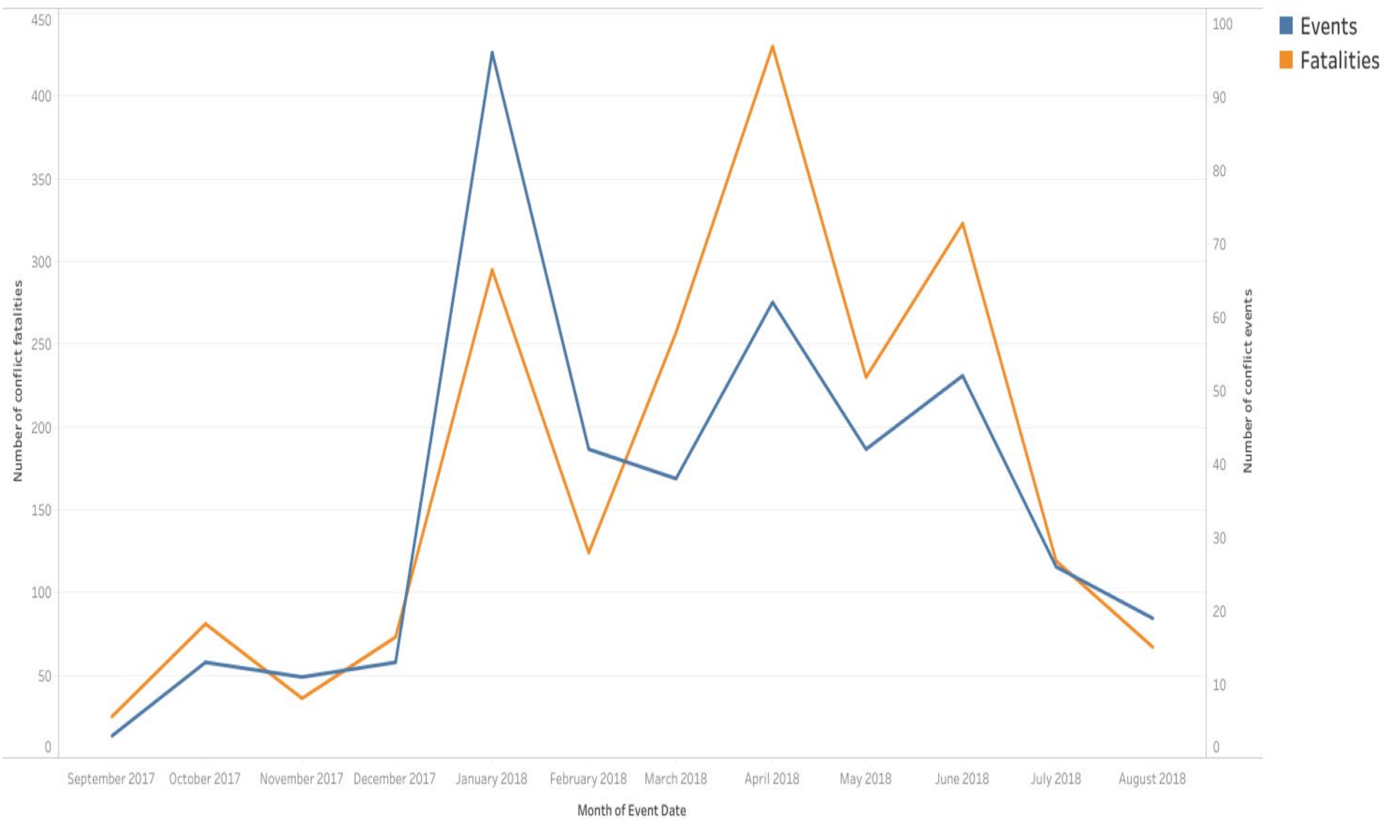
Contrary to our hypothesis, conflict does not have any impact on child dietary diversity irrespective of whether they are from farm households or non-farm households. Dietary diversity represents the quality of children nutritional intake, albeit it does not fully reflect a child’s food security status. This may suggest that conflict affects child food security through channels other than food security. Hence policymakers should focus on other channel through which conflict may affect children other than through food security such as access to healthcare facilities to mitigate the impact of conflict on children health outcomes.

Moreover, our findings also show that conflict only affect the WAZ and HAZ scores of children from farm households. This finding also implies that the impact of the conflict is more focused to farm communities and widespread impact if there is any is either short-lived or not substantial enough to affect the anthropometric measures of children living in non-farm households. Therefore, policymakers should focus on providing targeted support to farm communities affected by conflict, rather than trying to address the issue on a widespread scale.

In addition, our result indicates that farm households recover after conflict as children from farm households born after conflict have better anthropometric measures than their peers. Hence, policies that support the recovery of farm households after conflict can help improve the anthropometric measures of children in these households faster.

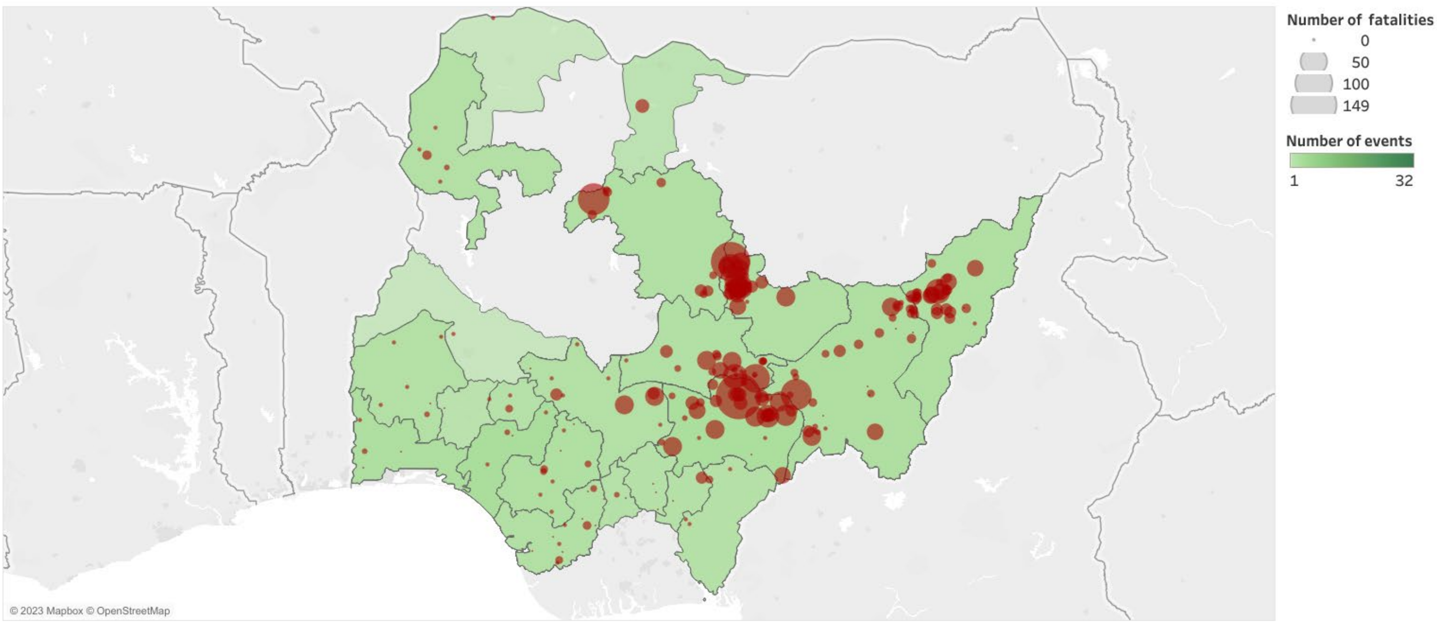
Appendix A

Figure A1: Farmer herder conflict events and fatalities from September 2017 to August 2018



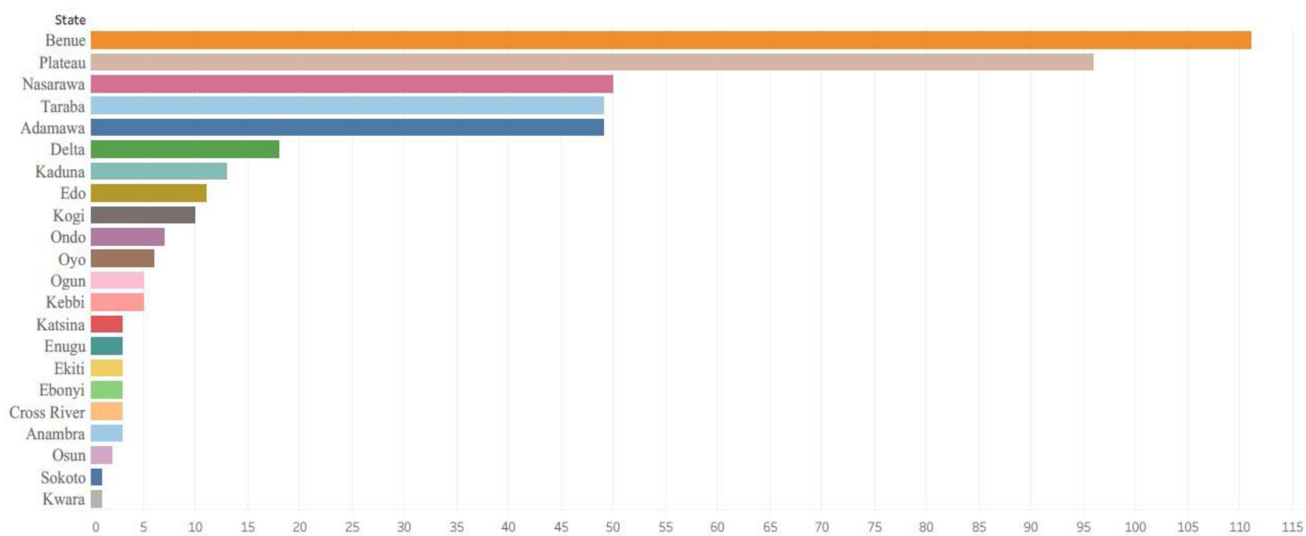
Source: ACLED (2023)

Figure A2: Spatial variation in farmer herder conflict events and fatalities from September 2017 to December 2018.



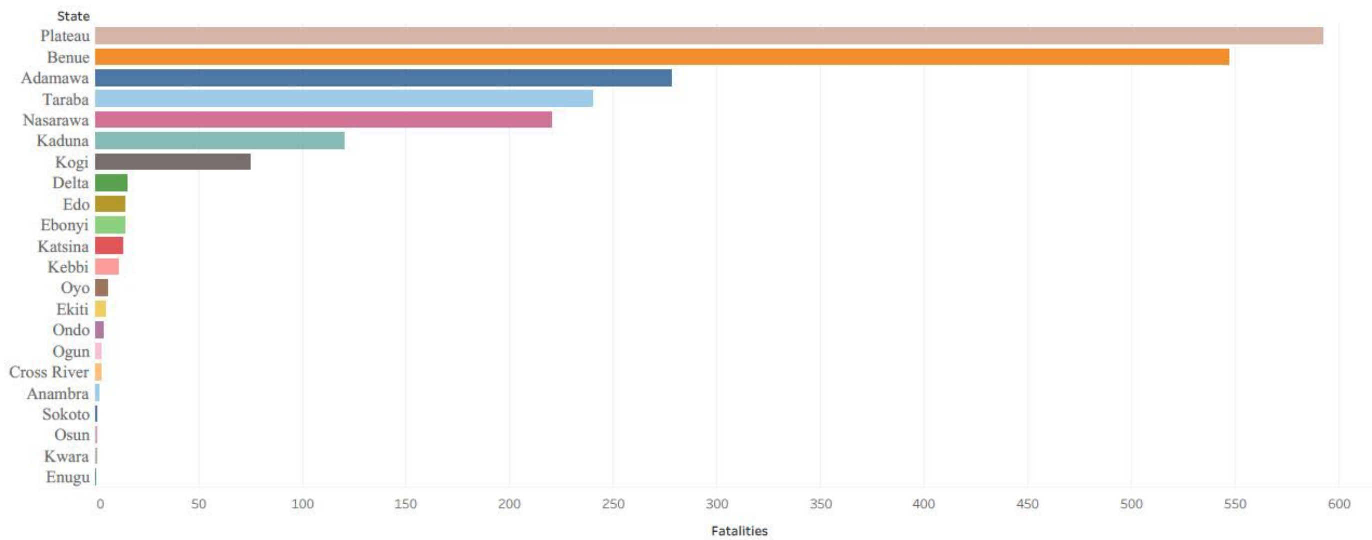
Source: ACLED (2023)

Figure A3: Number of conflict events by state between September 2017 and December 2018



Source: ACLED (2023)

Figure A4: Number of conflict fatalities by state between September 2017 and December 2018



Source: ACLED (2023)

Table A1: Summary statistics of dependent and independent variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Dependent variables					
MDD score	749	3.037	2.000	0	9
WAZ score	875	-0.704	1.232	-5.78	3.64
WHZ score	870	-0.123	1.132	-4.5	4.11
HAZ score	869	-1.048	1.405	-5.4	4.08
Independent variables					
Individual characteristics					
Child's age in months	885	23.189	17.183	0	59
Female child	885	0.496	0.500	0	1
Mother's education level	885	1.716	0.869	0	3
Household characteristics					
Non-Fulani households	885	1.000	0.000	1	1
Farm households	885	0.325	0.469	0	1
Household wealth index	885	2.934	1.357	1	5
Household head years of education	815	5.148	1.315	1	7
Household head age	885	40.849	13.071	18	87
Female household head	885	0.150	0.358	0	1
Household size	885	5.982	2.629	2	23
Number of children in the household	885	2.191	0.960	0	7
Cluster characteristics					
Rural clusters	885	0.324	0.468	0	1
Number of conflict incidence in cluster	885	1.584	2.801	0	27
Number of conflict fatalities in cluster	885	5.653	14.258	0	105

Table A2: Difference in means of households in the born after conflict cohort and alive during conflict cohort.

Variable	Born After Conflict	Alive during conflict	Difference
Conflict exposure	0.649	0.592	-0.052
	(0.481)	(0.492)	(0.072)
Non-Fulani households	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
Farm households	0.149	0.342	0.053
	(0.358)	(0.475)	(0.033)
Household wealth index	3.162	2.966	-0.022
	(1.335)	(1.361)	(0.098)
Household head years of education	5.169	5.171	0.061
	(1.298)	(1.306)	(0.124)
Rural households	0.257	0.342	0.000
	(0.440)	(0.475)	(0.000)
Number of Households	74	500	575

Table A3: Effects of conflict on child's dietary diversity score

	MDD	MDD	MDD	MDD	MDD	MDD
Survey during conflict	0.227	0.171	0.133	0.174	0.096	0.201
	(0.324)	(0.378)	(0.403)	(0.424)	(0.406)	(0.432)
Exposed cluster	0.181	0.083	0.027	0.033	0.075	0.140
	(0.204)	(0.257)	(0.261)	(0.304)	(0.269)	(0.311)
Survey during conflict * Exposed cluster	-0.287	0.021	-0.058	-0.177	-0.097	-0.484
	(0.446)	(0.498)	(0.659)	(0.735)	(0.668)	(0.750)
Farm household			-0.168	-0.392	-0.326	-0.325
			(0.460)	(0.589)	(0.474)	(0.596)
Survey during conflict * Farm household			0.353	-0.030	0.438	-0.266
			(0.638)	(0.833)	(0.644)	(0.853)
Exposed cluster * Farm household			0.549	0.350	0.415	-0.113
			(0.516)	(0.732)	(0.545)	(0.760)
Survey during conflict * Exposed cluster * Farm household			-0.759	0.343	-0.620	0.791
			(1.095)	(1.368)	(1.106)	(1.402)
Child's age		**-0.023*** **		**-0.024*** **		**-0.024*** **
		(0.005)		**(0.005)**		**(0.005)**
Female child		0.002		0.006		0.004
		(0.148)		(0.148)		(0.149)
Household head age		-0.008		-0.006		-0.010
		(0.039)		(0.040)		(0.040)
Household head age^2		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Female household head		-0.020		-0.016		0.015
		(0.229)		(0.237)		(0.237)
Household size		**-0.101** **		**-0.099** **		**-0.087* **
		(0.045)		**(0.045)**		**(0.045)**
Number of children		0.121		0.125		0.137
		(0.104)		(0.105)		(0.106)
Household head years of education		-0.011		-0.021		-0.073
		(0.100)		(0.103)		(0.109)
Mother's education level		0.089		0.098		0.086
		(0.106)		(0.107)		(0.107)
Household wealth index		0.184		0.194		**0.245* **
		(0.122)		(0.127)		**(0.135)**
Number of conflict incidence		0.048		0.036		0.056
		(0.081)		(0.084)		(0.085)
Number of conflict fatalities		-0.023		-0.024		**-0.028* **
		(0.015)		(0.016)		**(0.016)**
Month of survey fixed effect	No	No	No	No	Yes	Yes
Constant	2.885***	3.353***	2.928***	3.407***	2.973***	3.615***
	(0.194)	(1.106)	(0.264)	(1.144)	(0.267)	(1.155)
R-squared	0.161	0.191	0.157	0.187	0.158	0.192
Number of children	749	687	749	687	749	687

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effects of conflict on child Weight-for-Age Z-score

	WAZ	WAZ	WAZ	WAZ	WAZ	WAZ
Alive during conflict	-0.573**	-0.698**	-0.875***	-0.754**	-0.854***	-0.740**
	(0.249)	(0.287)	(0.285)	(0.308)	(0.289)	(0.313)
Exposed cluster	-0.215	-0.270	-0.564*	-0.515	-0.548*	-0.518
	(0.278)	(0.312)	(0.308)	(0.332)	(0.311)	(0.336)
Alive during conflict * Exposed cluster	0.286	0.456	0.789**	0.692**	0.772**	0.691*
	(0.294)	(0.325)	(0.332)	(0.350)	(0.334)	(0.354)
Farm household			-1.289**	-0.796	-1.247**	-0.868
			(0.597)	(0.818)	(0.606)	(0.832)
Alive during conflict * Farm household			1.266**	0.570	1.227**	0.660
			(0.585)	(0.797)	(0.594)	(0.809)
Exposed cluster * Farm household			2.219***	2.398**	2.185***	2.485***
			(0.717)	(0.941)	(0.725)	(0.954)
Alive during conflict * Exposed cluster * Farm household			**-2.677*** **	**-2.258** **	**-2.635*** **	**-2.343** **
			(0.744)	**(0.936)**	**(0.752)**	**(0.949)**
Child's age		0.001		0.001		0.000
		(0.003)		(0.003)		(0.003)
Female child		0.083		0.077		0.068
		(0.087)		(0.087)		(0.088)
Household head age		0.018		0.021		0.023
		(0.023)		(0.023)		(0.024)
Household head age^2		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Female household head		-0.011		-0.015		-0.008
		(0.135)		(0.135)		(0.137)
Household size		0.024		0.017		0.018
		(0.025)		(0.025)		(0.026)
Number of children		**-0.110***		-0.095		-0.094
		(0.060)		(0.060)		(0.060)
Household head years of education		-0.045		-0.048		-0.049
		(0.059)		(0.059)		(0.060)
Mother's education level		**0.116***		**0.111***		**0.106***
		(0.060)		**(0.060)**		**(0.061)**
Household wealth index		**0.200*** **		**0.210*** **		**0.214*** **
		(0.073)		**(0.074)**		**(0.075)**
Number of conflict incidence		-0.038		-0.047		-0.043
		(0.045)		(0.046)		(0.046)
Number of conflict fatalities		0.009		0.009		0.009
		(0.009)		(0.009)		(0.009)
Month of birth fixed effect	No	No	No	No	Yes	Yes
Constant	-0.220	-1.021	0.082	-0.969	0.060	-1.020
	(0.235)	(0.701)	(0.270)	(0.706)	(0.273)	(0.714)
R-squared	0.111	0.134	0.125	0.144	0.118	0.134
Number of children	875	805	875	805	875	805

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Effects of conflict on child Weight-for-Height Z-score

	WHZ	WHZ	WHZ	WHZ	WHZ	WHZ
Alive during conflict	-0.470**	-0.634**	-0.482*	-0.640**	-0.514*	-0.689**
	(0.237)	(0.274)	(0.274)	(0.297)	(0.276)	(0.300)
Exposed cluster	-0.123	-0.235	-0.168	-0.307	-0.199	-0.372
	(0.263)	(0.298)	(0.295)	(0.319)	(0.296)	(0.320)
Alive during conflict * Exposed cluster	0.145	0.187	0.266	0.273	0.292	0.326
	(0.279)	(0.309)	(0.317)	(0.336)	(0.318)	(0.338)
Farm household			-0.169	-0.235	-0.231	-0.432
			(0.567)	(0.775)	(0.573)	(0.782)
Alive during conflict * Farm household			0.044	0.095	0.105	0.275
			(0.554)	(0.754)	(0.559)	(0.759)
Exposed cluster * Farm household			0.524	0.755	0.619	1.038
			(0.677)	(0.888)	(0.681)	(0.893)
Alive during conflict * Exposed cluster * Farm household			-0.779	-0.789	-0.839	-1.006
			(0.704)	(0.885)	(0.707)	(0.890)
Child's age		**0.006****		**0.006****		**0.006****
		(0.003)		**(0.003)**		**(0.003)**
Female child		-0.027		-0.030		-0.056
		(0.082)		(0.082)		(0.083)
Household head age		-0.004		-0.004		-0.002
		(0.022)		(0.022)		(0.022)
Household head age^2		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Female household head		0.028		0.023		0.007
		(0.127)		(0.128)		(0.129)
Household size		0.042*		0.039		0.037
		(0.024)		(0.024)		(0.024)
Number of children		-0.081		-0.074		-0.067
		(0.056)		(0.057)		(0.057)
Household head years of education		-0.043		-0.040		-0.042
		(0.055)		(0.056)		(0.056)
Mother's education level		0.077		0.071		0.064
		(0.057)		(0.057)		(0.057)
Household wealth index		0.052		0.048		0.061
		(0.069)		(0.070)		(0.071)
Number of conflict incidence		**0.084****		**0.083***		**0.094****
		(0.042)		**(0.043)**		**(0.043)**
Number of conflict fatalities		-0.011		-0.011		**-0.014***
		(0.008)		(0.008)		**(0.008)**
Month of birth fixed effect	No	No	No	No	Yes	Yes
Constant	0.292	0.419	0.348	0.462	0.375	0.467
	(0.224)	(0.661)	(0.261)	(0.671)	(0.263)	(0.674)
R-squared	0.081	0.094	0.082	0.092	0.086	0.096
Number of children	870	800	870	800	870	800

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Effects of conflict on child Height-for-Age Z-score

	HAZ	HAZ	HAZ	HAZ	HAZ	HAZ
Alive during conflict	-0.879***	-0.682**	-1.198***	-0.987***	-1.102***	-0.899**
	(0.287)	(0.301)	(0.335)	(0.349)	(0.339)	(0.354)
Exposed cluster	-0.243	-0.175	-0.657*	-0.601	-0.602	-0.545
	(0.320)	(0.356)	(0.364)	(0.393)	(0.366)	(0.395)
Alive during conflict * Exposed cluster	0.292	0.308	0.845**	0.806**	0.789**	0.763*
	(0.340)	(0.354)	(0.390)	(0.403)	(0.391)	(0.405)
Farm household			-1.043	-0.844	-0.971	-0.773
			(0.653)	(0.684)	(0.659)	(0.690)
Alive during conflict * Farm household			1.101*	1.091	0.968	0.940
			(0.649)	(0.665)	(0.656)	(0.674)
Exposed cluster * Farm household			2.159***	2.381***	2.035**	2.220**
			(0.794)	(0.861)	(0.802)	(0.877)
Alive during conflict * Exposed cluster * Farm household			**-2.602*** **	**-2.667*** **	**-2.499*** **	**-2.507*** **
			(0.821)	**(0.880)**	**(0.829)**	**(0.894)**
Child's age		**-0.007** **		**-0.008** **		**-0.007** **
		(0.003)		**(0.003)**		**(0.003)**
Female child		**0.229** **		**0.210** **		**0.226** **
		(0.101)		**(0.101)**		**(0.103)**
Household head age		0.034		0.037		0.039
		(0.027)		(0.027)		(0.027)
Household head age^2		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Female household head		-0.061		-0.093		-0.050
		(0.157)		(0.159)		(0.160)
Household size		-0.024		-0.024		-0.021
		(0.033)		(0.033)		(0.034)
Number of children		-0.074		-0.063		-0.068
		(0.073)		(0.073)		(0.074)
Household head years of education		-0.088		-0.105		-0.099
		(0.066)		(0.066)		(0.067)
Mother's education level		0.043		0.053		0.055
		(0.072)		(0.072)		(0.072)
Household wealth index		**0.167***		**0.173***		**0.175***
		(0.086)		**(0.092)**		**(0.093)**
Number of conflict incidence		-0.122		-0.144		-0.159
		(0.125)		(0.126)		(0.128)
Number of conflict fatalities		0.005		0.009		0.012
		(0.016)		(0.016)		(0.016)
Semi annual period lapsed		-0.122		-0.147		-0.123
		(0.139)		(0.139)		(0.141)
Semi annual period lapsed2		0.008		0.012		0.010
		(0.021)		(0.021)		(0.021)
Constant	-0.273	-0.855	0.020	-0.655	-0.047	-0.830
	(0.271)	(0.816)	(0.318)	(0.864)	(0.320)	(0.877)
R-squared	0.099	0.109	0.109	0.117	0.107	0.113
Number of children	858	788	858	788	858	788

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table A7: Potential mechanisms of farmer herder conflict impact

	Number of visits	Prenatal care
Alive during conflict	-1.324	-0.053
	(0.922)	(0.077)
Exposed cluster	-0.873	-0.064
	(0.959)	(0.080)
Alive during conflict * Exposed cluster	0.861	0.091
	(1.076)	(0.090)
Farm household	-4.110**	-0.109
	(2.074)	(0.174)
Alive during conflict * Farm household	2.193	0.029
	(2.055)	(0.172)
Exposed cluster * Farm household	4.367*	0.368*
	(2.290)	(0.192)
Alive during conflict * Exposed cluster * Farm household	-3.671	**-0.401****
	(2.434)	**(0.204)**
Constant	9.529***	0.875***
	(3.106)	(0.260)
R-squared	0.319	0.219
Number of children	537	537

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Potential mechanisms of farmer herder conflict impact (contd.)

	Financial issues	Distance to health care facility	Not wanting to travel alone	Mother's MDD
Exposed cluster	0.010	0.090***	-0.049**	0.279
	(0.027)	(0.021)	(0.024)	(0.247)
Farm household	-0.383***	-0.022	0.098***	-0.628
	(0.055)	(0.042)	(0.031)	(0.516)
Exposed cluster * Farm household	**0.121****	**-0.199*****	**0.065***	-0.086
	(0.060)	**(0.046)**	**(0.034)**	(0.632)
Survey during conflict				0.126
				(0.352)
Survey during conflict * Exposed cluster				-0.262
				(0.592)
Survey during conflict * Farm household				-0.101
				(0.719)
Survey during conflict * Exposed cluster * Farm household				0.885
				(1.159)
Constant	0.308	0.132	0.189	2.336
	(0.207)	(0.159)	(0.117)	(1.511)
R-squared	0.769	0.812	0.865	0.328
Number of children	815	815	815	815

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A5: Effect of conflict on child Weight-for-Age Z-score in farm households

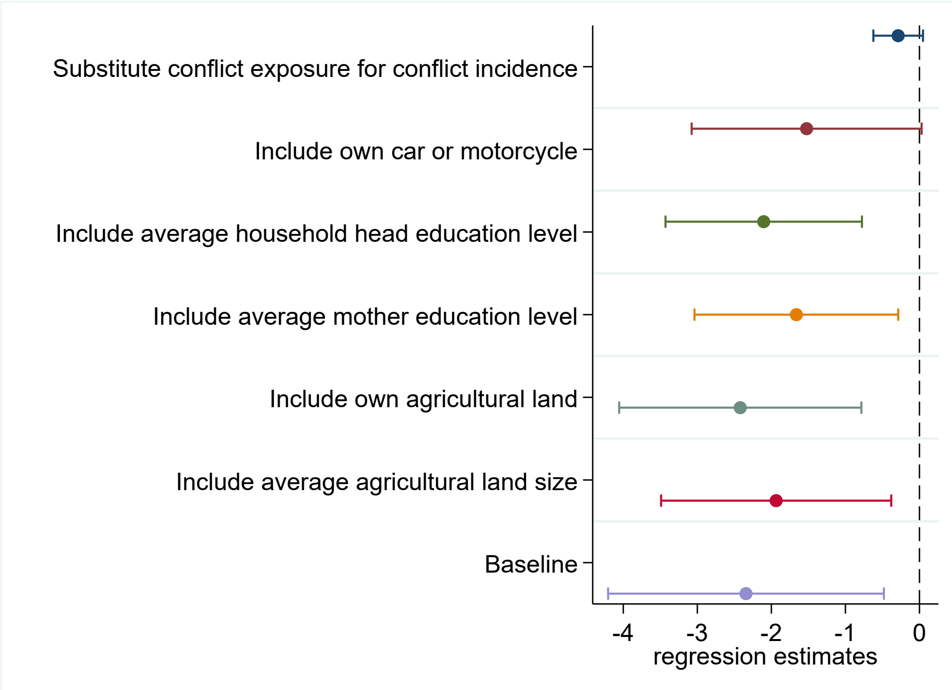
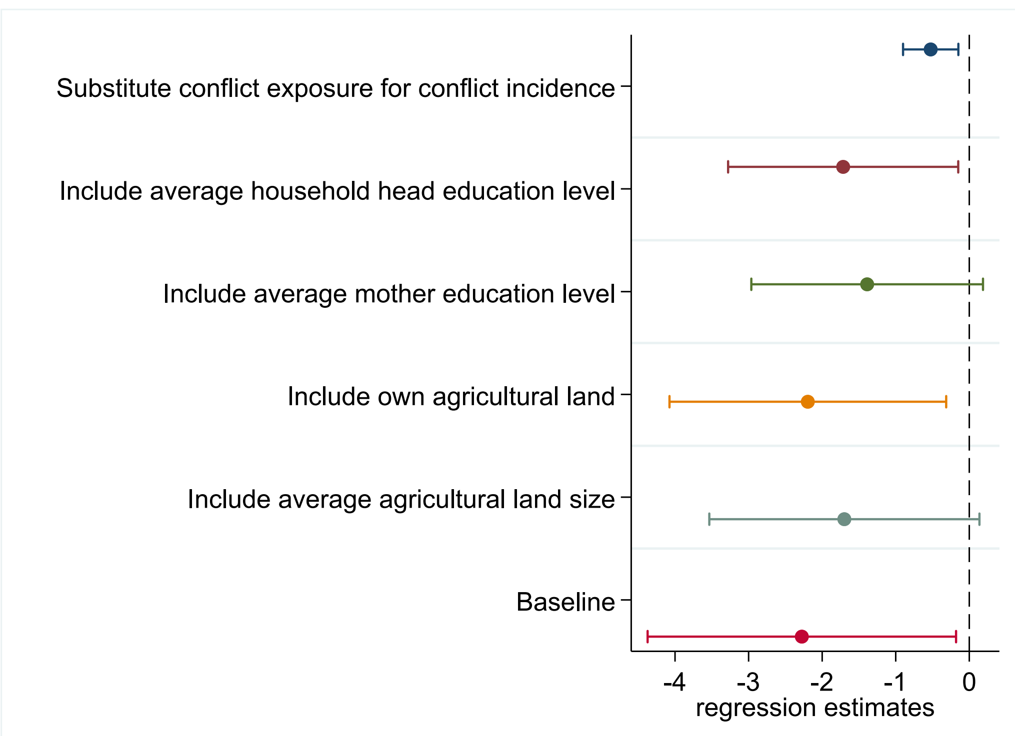


Figure A6: Effect of conflict on child Height-for-Age Z-score in farm households



Appendix B

Difference in means of household characteristics by matching methods.

i. **No matching**

For this matching method, exposed clusters are not matched to unexposed clusters. We ran our main regression analysis using the no matching sample with cluster strata fixed effect. The cluster strata variable in the DHS dataset categorizes clusters based on their state, geographical region within the state, and rural or urban status. Hence, clusters that share these characteristics are grouped into the same cluster stratum. For instance, if clusters 1, 2, and 3 are located in the rural region of the northern area of Adamawa state, they would be grouped into the same cluster strata. While this strategy allows the control of differences across cluster strata, it may not control for cluster non-geographical characteristics such as the wealth or occupation of households living in the cluster, which could cause endogeneity bias.

Table B1 shows the difference in means of household level covariates that could affect cluster conflict exposure in conflict exposed cluster and unexposed cluster. A majority of the 3163 households in the no-matching sample live in unexposed clusters while only about 17% are living in conflict-exposed clusters. Although there are no statistically significant differences in the proportion of non-Fulani households and rural households between conflict-exposed clusters and unexposed clusters, the average household wealth index in conflict-exposed clusters is higher than that of unexposed clusters.

Moreover, the average proportion of farm households is higher in unexposed clusters compared to conflict exposed clusters. This implies that conflict-exposed clusters differ from unexposed clusters in characteristics that could affect both the outcome variables and clusters' conflict exposure. Hence, there is a need to implement matching methods that facilitates the balance between conflict-exposed clusters and unexposed clusters in term of covariates that could cause endogeneity bias.

Table B1: No matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.923	0.951	-0.020
	(0.267)	(0.216)	(0.015)
Farm households	0.383	0.251	-0.133***
	(0.486)	(0.434)	(0.024)
Household wealth index	2.990	3.151	0.278***
	(1.435)	(1.369)	(0.069)
Household head years of education	4.989	5.039	-0.065
	(1.456)	(1.379)	(0.091)
Rural households	0.625	0.369	0.000
	(0.484)	(0.483)	(0.000)
Number of children	3383	897	4280
Number of households	2,634	529	3,163
Number of clusters	1060	158	1218

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ii. **Near matching**

For this matching method, we matched conflict-exposed clusters to the nearest unexposed clusters using the geodetic distance between clusters' geo-coordinates. The motivation for this method is that matched clusters that are close in proximity are likely to share many similar traits. The near matching method is the only matching method in this study that matches control clusters to treated clusters with replacement. Thus implying, a control cluster may be matched to more than one treated cluster.

However, the flaw with this strategy is that it cannot control for all cluster characteristics, which could result in endogeneity bias. For instance, a conflict-exposed urban cluster might be matched to an unexposed rural cluster because it is the closest in proximity to the conflict-exposed cluster. This is demonstrated in Table B2 where the average proportion of farm households and rural households in conflict-exposed clusters and unexposed clusters differ significantly by 13% and 21% respectively. The near-matching method does not fare any better compared to the no matching strategy in terms of the number of balanced covariates between conflict-exposed clusters and unexposed clusters. Moreover, the sample size is considerably lower in the near-matching scenario compared to the no matching scenario, while the number of conflict-exposed households remains unchanged.

Table B2: Near matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.961	0.955	-0.003
	(0.193)	(0.208)	(0.015)
Farm households	0.451	0.306	-0.125***
	(0.498)	(0.461)	(0.034)
Household wealth index	2.994	3.221	-0.009
	(1.362)	(1.334)	(0.093)
Household head years of education	5.171	4.953	-0.235*
	(1.396)	(1.495)	(0.140)
Rural households	0.543	0.369	-0.214***
	(0.499)	(0.483)	(0.024)
Number of children	1210	897	2107
Number of households	335	529	864
Number of clusters	125	158	283

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

iii. **P-score matching**

For this method, we ran a probit regression using the conflict exposure variable as the dependent variable and the matching variables as independent variables. Then we ran our main regression analysis by restricting the sample to observations that are within common support. This method facilitates the matching of clusters based on having a similar probability of exposure to farmer-herder conflict events given the matching variables**.** However, there are statistically significant differences in means of matching covariates between conflict exposed and the matched unexposed clusters as reported in Table B3. Further, we attempted to exact-match clusters by their cluster strata and then conduct a p-score matching within each cluster strata. However, this resulted in a very small sample within common support.

Table B3: Propensity score matching scenario.

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.980	0.949	-0.035***
	(0.140)	(0.219)	(0.010)
Farm households	0.418	0.249	-0.115***
	(0.494)	(0.433)	(0.024)
Household wealth index	3.068	3.144	0.233***
	(1.372)	(1.356)	(0.074)
Household head years of education	5.100	5.039	-0.065
	(1.392)	(1.379)	(0.088)
Rural households	0.505	0.354	0.000
	(0.500)	(0.479)	(0.000)
Number of children	1064	874	1938
Number of households	849	514	1,363
Number of clusters	352	150	502

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

iv. **Matching Algorithm**

For this method, all matching covariates except the cluster strata variable were converted into cluster-level covariates by taking the mean of the covariate for each cluster. For instance, the average household wealth index in a cluster is a cluster-level covariate derived by taking the mean of household wealth index for all households in the cluster. The cluster-level covariates are then converted into categorical covariates. A strata variable was generated using the categorical cluster-level matching variables. Strata that contain at least one conflict exposed cluster and at least one unexposed cluster are kept, and strata with either only conflict exposed cluster(s) or only unexposed cluster(s) are removed from the sample. The strata variable was used as a fixed effect in the main regression analysis. The difference in means in the matching covariates between conflict-exposed clusters and unexposed clusters is reported in Table B4. One half of the 360 households in the matching algorithm sample are in conflict-exposed clusters. All the matching covariates are balanced between both conflict exposure groups except for the average household wealth index in cluster, conflict exposed clusters have lower average household wealth index compared to unexposed clusters. While the matching algorithm scenario fares better than the no-matching scenario in terms of balance covariates, the matching algorithm sample size is only a small fraction of the no-matching sample. The small sample size could prevent the detection of a true effect.

Table B4: Matching algorithm scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
Farm households	0.272	0.322	-0.007
	(0.446)	(0.469)	(0.017)
Household wealth index	3.072	3.017	0.226*
	(1.329)	(1.253)	(0.116)
Household head years of education	5.291	5.256	0.020
	(1.283)	(1.219)	(0.091)
Rural households	0.322	0.378	-0.000
	(0.469)	(0.486)	(0.000)
Number of children	221	298	519
Number of households	180	180	360
Number of clusters	73	50	123

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

v. **Coarsened exact matching.**

Similar to the matching algorithm scenario, the cluster strata variable and categorical versions of the cluster-level matching variables were used to implement this matching method. Following this, the categorical covariates were subjected to an exact matching algorithm to identify the matched clusters and remove unmatched clusters. The CEM algorithm generates a set of strata with uniform values for each categorical covariate within each stratum. Clusters in strata that contain at least one conflict exposed cluster and unexposed cluster are kept while clusters in the remaining strata are removed from the sample. Table B5 reveals that of the 1226 households in the coarsened exact match sample, about 35% are in the conflict-exposed clusters. All matching covariates are balanced between conflict-exposed clusters and unexposed clusters except the average proportion of rural households and farm households.

Table B5: Coarsened exact matching scenario.

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.980	0.966	-0.002
	(0.141)	(0.183)	(0.005)
Farm households	0.245	0.241	-0.049***
	(0.431)	(0.428)	(0.015)
Household wealth index	3.568	3.299	0.048
	(1.377)	(1.357)	(0.048)
Household head years of education	5.075	5.025	0.097
	(1.405)	(1.371)	(0.074)
Rural households	0.480	0.333	-0.136***
	(0.500)	(0.472)	(0.024)
Number of children	1014	733	1747
Number of households	791	435	1,226
Number of clusters	339	132	471

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

vi. Supported Score-based Neighborhood matching

For this matching strategy, a probit regression was conducted using cluster-level covariates including the cluster strata variable. Using the propensity score predicted from the probit regression, the ultimatch command in STATA was employed to conduct a neighborhood matching on the sample that is on common support while specifying an exact matching on cluster strata. The supported score-based neighborhood matching method matched conflict-exposed clusters to unexposed clusters without replacement. Table B6 presents difference in means of matching covariates between conflict-exposed clusters and unexposed clusters in the score based neighborhood-matching sample. About 57% of the 563 households in the neighborhood-matching sample are in conflict-exposed clusters. Further, there are statistically significant differences in the proportion of non-Fulani households, farm households and average household wealth index between conflict-exposed clusters and unexposed clusters.

Table B6: Supported Score-based Neighborhood matching scenario

Variable	(1) Control group	(2) Treatment group	(3) Difference
Non-Fulani households	0.971	0.919	-0.050***
	(0.168)	(0.274)	(0.013)
Farm households	0.395	0.244	-0.135***
	(0.490)	(0.430)	(0.021)
Household wealth index	2.885	3.253	0.404***
	(1.287)	(1.290)	(0.081)
Household head years of education	5.222	5.013	0.074
	(1.303)	(1.393)	(0.070)
Rural households	0.395	0.397	-0.000
	(0.490)	(0.490)	(0.000)
Number of children	309	534	843
Number of households	243	320	563
Number of clusters	103	91	194

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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